Expert Systems in Manufacturing

B.R. GAINES
University of Calgary
Calgary, Alberta

Gaines, B. R. (1986). Expert systems in manufacturing. In Proceedings of AUTOFACT'86, pp. 8-45-8-62. Society of Manufacturing Engineers, Dearborn, Michigan.

The development of expert systems technology and applications is reviewed with particular attention to applications in manufacturing. Technical aspects of acquiring, encoding, and applying knowledge and key achievements of expert systems applications are reviewed. The main features of the different approaches to system development involved in expert systems and the role of different information technologies in manufacturing and their relations to expert systems are described.

1. INTRODUCTION

Major new opportunities have arisen in manufacturing:

- **Automation**: new levels of maturity in automation have reduced the effect of unit labor costs and emphasized effective equipment investment
  - — labor costs need no longer be criticial competetive factors
  - — it is possible to be competetive without relocating to remote territories
  - — effective equipment investment is critical to a competetive position.
- **Flexibility**: robotics and flexible automation enable short-run manufacturing and mass-production to be comparable in unit costs
  - — large production units can compete with small job shops for small volume products
  - — small job shops can compete with large production units for high volume products.

With the new opportunities are associated new problems:

- **Economic change**: the reduced sensitivity to labor costs and batch size changes the economic foundations of manufacturing
  - — it moves the competetive edge elsewhere.
- **New frameworks**: companies that only perceive the impact of the new technology on their existing business are likely to be deceived
  - — the conceptual framework for manufacturing has changed.
- **Critical factors**: operating factors that have been of secondary significance now become dominant
  - — administrative overheads
  - — inventory costs
  - — effective communications with suppliers
  - — effective communications with customers.
- **Integration**: this leads to an emphasis on integrated systems in which information flows are adequate to support the overall optimization of the manufacturing unit
  - — new problems arise in the specification and design of integrated systems
  - — major new problems arise in the management of integrated systems.

The effective management of the new technology has become of major importance, replacing people management as a primary concern. The flexibility, customization and localization offered by integrated manufacturing systems (IMSs) are attractive but generate a new class of management problems (Sullivan 1985). The information flows required in manufacturing increase greatly with the diversity of product being handled and the rapidity of change between products. The knowledge required to manage these information flows is not readily available. Setting up a flexible production line requires different and higher-level skills than those required to operate it once running. Additional skills are required to design a flexible manufacturing system capable of handling a diversity of products (Gunn 1981, Morgan 1984, Kusiak, Vannelli & Kumar 1985).

Management support systems are needed for the planning, implementation, configuring and operation of IMSs (Elavia 1985, Miller 1985, Nassr 1985). Fortunately, and not as a mere coincidence, new information technologies are becoming available to provide such support. Expert systems (ESs) provide a technology to cope with the diversity and complexity of the information involved (Kempf 1985, Liu 1985, McDonald 1985). However, an ES alone cannot cope with the volume of information about different machine tools and robots, the computation required in grouping and the provision of numeric simulations for interactive planning and testing. An adequate support system for managing IMSs involves the combination of ES and simulation-based decision aids with numeric computation, databases, communications, and, if it is to be used in operations (Maimon 1985, Rhodes 1985, Spur & Mertins 1985), instrumentation and control systems.

This paper is concerned with expert systems, their essential nature, their role in manufacturing, their integration with other information technologies and the organization, and the problems involved in their development. The next section gives an overview of expert systems, and is followed by an analysis of the new approaches involved. Later sections cover the roles and interactions of different forms of information technology in supporting the management of a modern production unit.

2. EXPERT SYSTEMS: AN OVERVIEW

The computer simulation of people in the roles of experts on some topic has become an important application of interactive computer systems. It has generated a new industry based on creating expert systems to make the practical working knowledge of a human expert in a specific subject area such as medicine or geology widely available to those without direct access to the original expert (Reitman 1984). Programs now exist that have made practical achievements in medical diagnosis, interpretation of mass spectroscopy results, analysis of geological survey data, and other problems where one would normally go to a human expert for advice. This section gives an overview of expert systems and knowledge engineering.

2.1 EXPERT SYSTEM ARCHITECTURES AND KNOWLEDGE ENGINEERING

Figure 1 shows the basic architecture of an expert system:

Knowledge base: the central feature is a *knowledge base* of facts and inference rules.

Expert system shell: the lower oval shows the operational system for applying the knowledge base to decision support.

- The inference system derives the consequences of facts about a particular situation.
- The planning system determines how to use the inference system to satisfy the specified objectives.
- The explanation system answers questions about the basis of the inferences made.

Knowledge acquisition system: the upper oval shows the knowledge transfer processes that may be used to establish the knowledge base.

- The knowledge generation system implements knowledge acquisition by the raw induction of models from experience without cultural support as exemplified by ATOM (Gaines 1977) and AM (Davis & Lenat 1982).
- The expertise modeling system implements knowledge acquisition by mimicking an expert's behavior as exemplified by INDUCE (Michalski & Chilausky 1980).
- The performance reinforcement system implements knowledge acquisition from performance feedback as exemplified by STelLA (Gaines & Andreae 1966).
- The knowledge elicitation system implements knowledge acquisition by interviewing experts as exemplified by PLANET (Shaw & Gaines 1983) and ETS (Boose 1985).

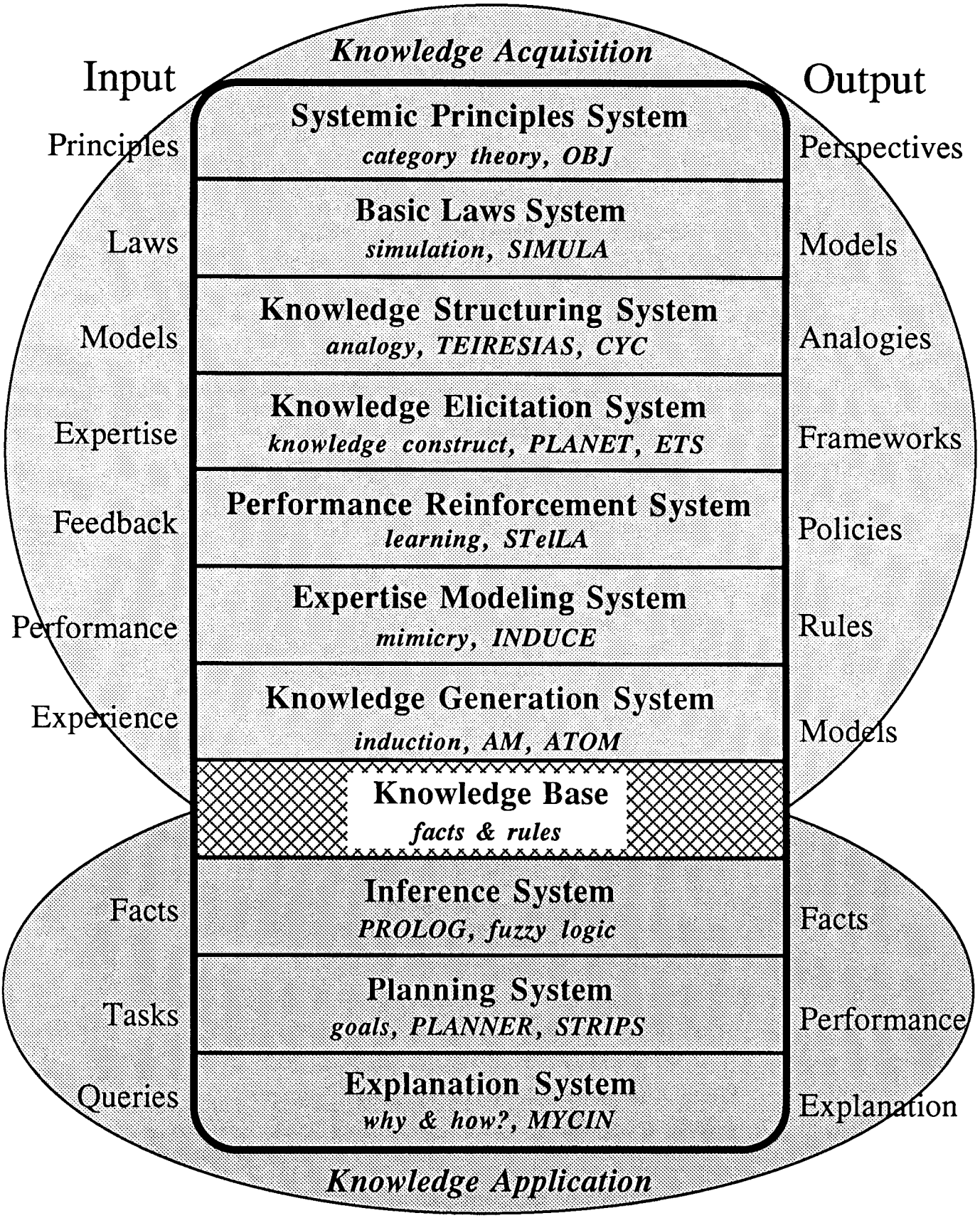

Fig.1 Basic architecture of an expert system

- The knowledge structuring system implements knowledge acquisition by analogy as exemplified by TEIRESIAS (Davis & Lenat 1982) and CYC (Lenat, Prakash & Shepherd 1986).
- The basic laws system implements knowledge acquisition by building physical models as exemplified by simulation languages such as SIMULA (Nygaard & Dahl 1981).
- The systemic principles system implements knowledge acquisition by derivation from abstract principles as exemplified by the category-theoretic language OBJ (Goguen & Meseguer 1983).

Most current expert system shells offer a limited knowledge base represented in terms of production rules and frames, have weak planning capabilities limited to derving consequences and testing assertions, and give simple explanations in terms of the facts and rules used. Most current knowledge acquisition is done by manual knowledge elicitation at the level highlighted. However, automatic tools for rapid prototyping are becoming increasingly important (Gaines & Shaw 1984b, 1985c,d, 1986c) and are described in a sister paper (Gaines & Shaw 1986d).

2.2 THE DEVELOPMENT OF EXPERT SYSTEMS TECHNOLOGY

One of the first ES developments was the *fuzzy logic* control system developed in 1974 by Mamdani and Assilian. The system accepted human knowledge of control strategies expressed verbally and encoded it directly as computer programs which acted on the environment (Mamdani & Assilian 1981). This work was undertaken as part of a study of machine learning in process control and the system controlled was a small steam engine. The verbal rules were of the form:

If the pressure error is positive and big and the change in pressure error is not negative medium or big
Then make the heat change negative and big

Fig. 2 Rule from fuzzy logic controller

Priming the learning machine by such rules was first introduced because learning took too long. It was expected that the rules would act like verbal instructions to a human operator and aid the machine in setting up an initial approximate control strategy. However, it was found that rules such as this may be interpreted algorithmically to produce computer control programs that are more effective than those derived from classical control theory. Additionally, the learning machine then proceeded only to "learn" less effective strategies. Hence interest switched to the process whereby human expression of verbal rules that appear vague can lead to highly effective control strategies, that is to the development of ESs.

The rules on which a particular ES is based may be seen as ways of representing knowledge. This is not a new concept as such rules have been used in the past quite independently of computer systems. Figure 3 is an excerpt from a training manual for lime kiln operators (Peray & Waddell 1972). It seems that the encoding of expertise into a set of fairly vague but highly applicable rules is a standard way of making it available to others.

1. When the burning zone temperature is drastically low:
   (a) reduce kiln speed;
   (b) reduce fuel.

2. When the burning zone temperature is slightly low:
   (a) increase I.D. fan speed;
   (b) increase fuel rate.

Fig. 3 Rules from a lime kiln operator's manual

In parallel with the controller development, other ESs were being developed for completely different domains. MYCIN is a well-known medical diagnosis ES which aids a clinician to act as a consultant on infectious diseases (Shortliffe 1976). It uses rules of the form shown in Fig.4. Such rules are obtained from specialists in microbial infections and their application to particular data is fairly simple data processing. The rules are validated through their application to many cases and revised when they fail to give the correct diagnosis. MYCIN is designed to interact with a clinician in order to make a diagnosis and suggest therapy for a particular patient with a suspected microbial infections. It first gathers data about the

RULE 50

If 1) the infection is primary-bacteremia, and
2) the site of the culture is one of the sterile sites, and
3) the suspected portal of entry of the organism is the gastro-intestinal tract,

Then there is suggestive evidence (.7) that the identity of the organism is bacteroides.

Fig. 4 A MYCIN rule

patient and then uses this to make inferences about the infections and their treatment. Fig. 5 shows part of a dialog between MYCIN and a clinician responsible for testing and treating a patient.

--------PATIENT-1--------
(1) Patient's name: (first-last)
****FRED SMITH**
(2) Sex:
****MALE**
(3) Age:
****55**
(4) Have you been able to obtain positive cultures from a site at which Fred Smith has an infection?
****YES**
--------INFECTION-1--------
(5) What is the infection?
****PRIMARY-BACTEREMIA**
(6) Please give the date and approximate time when signs or symptoms of the primary-bacteremia (INFECTION-1) first appeared. (mo/da/yr)
****MAY 5, 1975**
The most recent culture associated with the primary-bacteremia (INFECTION-1) will be referred to as:
--------CULTURE-1--------
(7) From what site was the specimen for CULTURE-1 taken?
****BLOOD**
(8) Please give the date and time when this blood culture (CULTURE-1) was obtained. (mo/da/yr)
****MAY 9, 1975**
The first significant organism from this blood culture (CULTURE-1) will be referred to as:
--------ORGANISM-1--------
(9) Enter the identity of ORGANISM-1:
****UNKNOWN**
(10) Is ORGANISM-1 a rod or coccus (etc.):
****ROD**
(11) The gram stain of ORGANISM-1:
****GRAMNEG**
(12) Have there been POSITIVE cultures from sites which are NOT associated with infections about which you are seeking advice?
****NO**
(13) Did ORGANISM-1 grow aerobically?
****YES (8)**
(14) Did ORGANISM-1 grow anaerobically?
****YES**
(15) What is the suspected portal of entry of ORGANISM-1 into the sterile site?
****GI (6)**

Fig. 5 Some interaction with MYCIN

2.3 THE SPREAD OF EXPERT SYSTEMS TECHNOLOGY

Since the initial success with MYCIN a very wide range of ESs have been developed. Fig. 6 is a brief summary of some significant expert systems and their applications.

DENDRAL	structure of chemical compounds from mass-spectral data and knowledge of mass spectrometry
META-DENDRAL	inferring rules of mass spectrometry
MYCIN	diagnosis of blood infections and recommendations for treatment
TEIRESIAS	knowledge acquisition and debugging
EMYCIN	empty (essential) MYCIN expert system shell
PUFF	EMYCIN with knowledge base for pulmonary function disorders
MOLGEN	scientist's assistant for planning experiments in molecular genetics
PROSPECTOR	assisting evaluation of geological prospects
CASNET	diagnosis of glaucoma (eye disease)
XCON (or R1)	system for configuring VAXs
INTERNIST	advisors for general internal medicine (can deal with symptoms and diagnose 500 diseases)
AM	automated mathematician discovers interesting conjectures in mathematics
CRYSALIS	infers protein structure from electron density maps

Fig. 6 Some significant expert systems

Figure 7 is a brief summary of some major areas of application of ESs (Gevarter 1983). The numbers and domains have both increased greatly since these tables were prepared as research and applications of ES have developed world-wide. It is now impossible to make any accurate count since most universities have some activity and many industrial expert systems are regarded as highly proprietary.

Analysis	electrical circuits, naval threat, mechanics, digital circuits, earthquake damage
Automatic programming	software generation
Concept formation	mathematics
Control	flexible manufacturing, lime kiln, smelting
Data analysis	geology, chemistry, protein crystallography, medicine, oil-well logs
Design	flexible manufacturing, computer system configuration, circuit, chemical synthesis
Diagnosis	medicine, computer faults, nuclear reactor accidents
Image analysis	weather forecasting, medical diagnosis
Instruction	electronics, mathematics, medical diagnosis, coaching, plant operation
Intelligent assistant	weapons assignment, medicine, radiology, computer sales, nuclear plant configuration
Knowledge acquisition	manufacturing, medical diagnosis, geology
Learning	plant diagnosis, chemistry, heuristics
Management	project, automated factory
Monitoring	industrial plant, patient respiration
Planning	chemical synthesis, robotics, molecular genetics, medical diagnosis, scheduling

Fig. 7 Applications of expert systems

2.4 THE IMPORTANCE OF META-KNOWLEDGE

MYCIN works well when the rules are complete and correct, but it was difficult to set up the rules initially. It was also difficult to trace the rules causing errors in the deductions of MYCIN if the clinician feels that something has gone wrong. To overcome these problems TEIRESIAS (Davis & Lenat 1982) was added as an auxiliary ES with expertise about MYCIN. It has the facility to explain MYCIN's decisions, and help the clinician amend the rules when they lead to incorrect conclusions.

TEIRESIAS uses a similar rule-based approach to reasoning as does MYCIN but the rules are now rules about the forms of rules and the use of rules. The rules of Figs. 2 through 4 are expressions of inferences from data about the world to conclusions about it, a basic level of knowledge processing. Davis discovered that similar rules could express inferences at a higher level about relations between these basic patterns of inference. A typical one of these *metarules* has the form:

METARULE003:
If 1) there are rules which do not mention the current goal in their premise
2) there are rules which mention the current goal in their premise
Then it is definite that the former should be done before the latter.

Fig. 8 A TEIRESIAS metarule

The effect of the metarules on the dialog is that the clinician and MYCIN/TEIRESIAS can discuss the rules and inferences made as well as the patient, organisms and infection. Figure 9 shows a debugging sequence in which MYCIN makes an incorrect inference and TEIRESIAS aids the clinician in correcting it.

My therapy recommendations will be based on the following probable infection(s) and potential causative organism(s):
INFECTION-1 is PRIMARY-BACTEREMIA
<Item 1> E.COLI [ORGANISM-1]
<Item 2> PSEUDOMONAS-AERUGINOSA [ORGANISM-1]
Are all these identities correct?
++** **N**
Are there any identities missing?
++** **Y**
Which one(s)?
++** **KLEBSIELLA-PNEUMONIAE PROTEUS-NON-MIRABILIS**
Are there any identities that shouldn't have appeared?
++** **Y**
Which one(s)?
++** **PSEUDOMONAS-AERUGINOSA**
Do you want to
1] track down the problem yourself, or
2] allow me to guide the debugging, or
3] ignore it for now and fix it another time?
Type 1, 2 or 3
++** **2**
We'll start with the PSEUDOMONAS-AERUGINOSA first. The following rules were used in deducing that the identity of ORGANISM-1 is pseudomonas-aeruginosa
RULE184
Since [1.1] the category of ORGANISM-1 is not known
[1.2] the gram strain of ORGANISM-1 is gramneg
[1.3] the morphology of ORGANISM-1 is rod
[1.4] the aerobicity of ORGANISM-1 is facultative
There is weakly suggestive evidence (.3) that the identity of ORGANISM-1 is pseudomonas-aeruginosa
Is this rule correct?
++** **Y**

Should its premise have failed for this case?
++** **Y**
Which clause of the premise should have been false? [give #]
++** **1**
No conclusions were reached concerning the category of ORGANISM-1. Should it have been possible to conclude a category?
++** **Y**
Which one?
++** **ENTEROBACTERIACEAE**
There were no rules successfully invoked in the attempt to deduce that the category of ORGANISM-1 is enterobacteriaceae.
The following (potentially applicable) rules were NOT executed because the starred [**] clause failed:
RULE116
If 1) the identity of ORGANISM-1 is not known
** 2) the gram strain of ORGANISM-1 is not known
3) the morphology of ORGANISM-1 is not known
4) the site of CULTURE-1 is csf
5) the infection is meningitis
6) the age (in years) of Albert Hall is less than or equal to .17
then there is weakly suggestive evidence (.33) that the category of ORGANISM-1 is enterobacteriaceae
RULE050
If 1) the morphology of ORGANISM-1 is rod
2) the gram strain of ORGANISM-1 is gramneg
3) the aerobicity of ORGANISM-1 is facultative
** 4) the infection with ORGANISM-1 was acquired while the patient was hospitalized **
then there is suggestive evidence (.7) that the category of ORGANISM-1 is enterobacteriaceae
Are all these rules correct?
++** **Y**
Should any of them have been successfully invoked?
++** **N**
Is there a rule missing?
++** **Y**
Ok, then I need a rule that would allow me to deduce that the category of ORGANISM-1 is enterobacteriaceae.
Would you like to give me such a rule now?
++** **Y**

Fig. 9 Changing MYCIN's knowledge base by interaction with TEIRESIAS

In this dialog the clinician noticed an identity was missing in those deduced by MYCIN. He chose to allow TEIRESIAS to guide the debugging, and it used the metarule of starting with the identity which appeared incorrectly. The program then reconstructed the deductive process, asking the clinician to confirm its actions at each stage, or comment on anything incorrect. It confirmed the facts about the particular case in hand and checked that the rules were correct. Before very long the issue has become sharply focused for the clinician and the system.

The main guideline in debugging MYCIN is that a rule must be found which is relevant to this particular patient, but true in general, and enhancing the set of rules of knowledge. The new rule is added to the set of knowledge rules, with a tag explaining who added it and in what circumstances. This allows the ultimate level of explanation to be given in terms of who added the rule and the reasons given. Whereas MYCIN's rules are specific to microbial infections, those of TEIRESIAS are more general and can be used in other domains. Davis (1983), for example, shows TEIRESIAS being used as an investment decision system for clients of a stockbroker.

2.5 INDUCTIVE ACQUISITION OF KNOWLEDGE

The interaction with TEIRESIAS demonstrates the dynamic nature of ESs. They have often been presented in the literature as means of capturing expert knowledge as if that knowledge was a static, finished product, universal in nature and owned by one person. In practice knowledge is fluid, situational and generally distributed across groups of people. The initial priming of an ES with the knowledge of one or more experts is a way of getting started. Metarules cannot be effective unless the basic vocabulary and patterns of inference have been at least approximately established. However, an ES then becomes an entity that grows with the knowledge and experience of its users. It is a support tool for their knowledge acquisition and refinement as well as a way of making it more accessible to themselves and others.

The use of metarules allows ES to be programmed interactively by their users. From one perspective TEIRESIAS can be seen as an important development in automatic programming. From another it can be seen as a way in which a machine acquires knowledge through interaction with a person. Metarules may also be used to implement knowledge acquisition procedures in which machines acquire knowledge directly through their interaction with the environment, i.e. a process of *machine learning* (Michalski & Carbonnel 1983).

Mamdani, Procyk and Baaklini (1976) found that learning could be introduced effectively in the steam engine controller through metarules that expressed the way in which the basic rules should be changed as a result of performance feedback. The learning level of their controller operator on rules of the form:

If time is small and error is negative big
Then desired change is big.

If time is big and error is positive zero
Then desired change is zero.

Fig. 10 Rules from fuzzy learning controller

The use of a very high level of metarules for knowledge acquisition is illustrated by AM (Davis & Lenat 1982) which searches for "interesting" conjectures in mathematics. What is remarkable about AM is the very notion of what it is doing. This is the highest level of scientific creation, looking for the patterns underlying knowledge. The concept of something being interesting seems peculiarly human and certainly too vague to form the basis of a computer program. However, AM is not only able to generate profound conjectures in mathematics but also meaningful ways of arriving at them. It is judged by the quality of its musings as it considers what it is doing.

Figure 11 shows two of the few hundred rules used by AM. Most of them are sufficiently general to apply to other situations. In an organizational context, for example, Rule 19 indicates that a committee which has decision-making powers that do not apply to its sub-committees below a certain size has an interesting property (that of requiring a quorum). Its sub-committees also have an interesting property (that of being quorate).

19. If concept C possesses some very interesting property lacked by one of its specializations S,
    Then both C and S become slightly more interesting.
38. If there are no known examples for the interesting concept X,
    Then consider spending some time looking for such examples.

Fig. 11 Two rules of high generality from AM

Inductive inference of knowledge through machine learning procedures is a significant alternative to direct access to the verbal knowledge of experts, and comes closer to capturing the knowledge of main interest. We want to know the basis for what the experts *do* rather than what they *say* they do. Michalski and Chilausky (1980) have reported an interesting comparison of two ESs for plant disease diagnosis, one constructed directly from the expert's stated rules, and the other constructed automatically by an algorithm for logical induction of structure from behavior. The ES with induced rules had a better performance in diagnosis and the expert agreed that its rules, although not obvious at first, were better than his own.

2.6 SUMMARY

Expert systems have developed in the past decade from experiments in artificial intelligence to a major commercial industry. They allow human expertise in knowledge representation and inference to be encoded for computers and used for problem-solving. They provide not only a static recording of expertise but also the capability to develop and extend that expertise and tailor it to local situations. Successful applications include not only high-level human cognitive skills such as medical diagnosis, but also important industrial control skills where people carry out tasks that could not be automated using previously available techniques. The most recent developments of ES include knowledge acquisition not only through interaction with experts but also through inductive inference from experience.

3. WHAT IS DIFFERENT ABOUT EXPERT SYSTEMS?

The previous section has shown how applications of expert systems to control and decision systems uses linguistic rules, approximate reasoning and metarules. It is clear that expert systems use some new computational techniques, but perhaps less apparent that the system design approach involved is itself fundamentally changed. However, major paradigm shifts are involved (Gaines & Shaw 1985b). The classical approach in decision and control system design is:

a) thoroughly instrument the system to be controlled or about which decisions are to be made;

b) use the instrumentation to gather data about the system behavior under a wide variety of circumstances;

c) from this data build a model of the system that accounts for this behavior;

d) from this model derive algorithms for decision or control that are optimal in terms of prescribed performance parameters.

Fig. 12 Classical approach to system design

This approach underlies the methodologies of the physical sciences and technologies based on them. It has the merit that it has been extremely successful in engineering much of the technological infrastructure of our current society including our maufacturing industries.

However, this approach is successful only to the extent that the systems under consideration are amenable to instrumentation and modeling. Its greatest successes have been where this amenability can be achieved normatively, that is in cases where the system to be controlled is itself a human artifact. For example, linear system theory has not become a major tool in systems engineering because most natural systems are linear—they are not. The implication is in the opposite direction: that linear systems are mathematically tractable and that we design artificial systems to be linear so that we may model them readily.

The application of "a linear model with quadratic performance criterion" to natural systems is often attempted but, in general, it does not work. We have done so not because the tool was appropriate, but because it was the only one we had. However, the use of a hammer to insert screws, although partially effective, tends to distort, destroy, and generally defeat the purpose of using a screw. Similarly, the use of an inappropriate system theory to model a system may give useful, but limited, results when we have no other, but it distorts reality, destroys information and generally defeats the purpose of modeling that system.

Much of our current technology succeeds to the extent that it is normative. In agriculture we reduce the complexity of a natural ecology to a comprehensible simplicity by the use of pesticides, herbicides and chemical fertilizers (Gaines & Shaw 1984c). We reduce the system to one which is amenable to our modeling techniques. That simpler is not necessarily better and that re-engineering nature to impose uniformity destroys variety which is itself valuable have only been realised in recent years.

The four shifts in perspective in expert systems are:

Problem 1: The models available are inadequate to capture the system.
Old Approach: *Procrustean Design.* Change the system to fit the model—normative technology.

Paradigm Shift: *Model Realism.* Use system methodologies and information technology that enable the system to be modeled without distortion and destruction.

Problem 2: Optimal control is over-sensitive to system uncertainties.

Old Approach: *Sub-Optimality.* Use a sub-optimal controller that is robust.

Paradigm Shift: *Model Uncertainty.* Model the uncertainty as part of the system.

Problem 3: Data is unavailable or inadequate for modeling.

Old Approach: *Managing.* Do not automate—leave to human decision/control.

Paradigm Shift: *Expert Systems.* Model the person as a decision-maker or controller.

Problem 4: Neither a human nor an automatic system alone is adequate.

Old Approach: *Ad Hoc System Design.* Use a mixture of automatic and human decision/control.

Paradigm Shift: *Accountable Integration.* Integrate automatic and human activity—make the automation accountable ("why?" in ES).

Fig. 13 Shifting paradigms in system design

The last three perspectives all stem from the first.

The second perspective is that which lead to new techniques for dealing with uncertainty and approxinate reasoning (Gupta et al 1985). Optimal control theory was regarded as the peak achievement of system theory in the 1950s and 1960s. However, it proved limited in application because it demanded precision in system modeling that was impossible in practice. It was too sensitive to the nuances of system structure expressed through over-precise system definition.

The third perspective is that which led to the success of linguistic fuzzy controllers and later ESs. Hayes-Roth (1984) has noted the many problems that have been felt to require human management are now amenable to ESs. Modeling the way the expert performs the task rather than modeling the task itself is the primary characteristic of an ES.

The fourth perspective is an important one for ES. They are knowledge-based systems because they make provision for explaining the decisions reached. The "why?" question has important implications for both the practical and theoretical significance of ESs and the logics on which they are based. ES represent new maturity in information technology by providing an audit trail of the data and inferences on which their recommendations are based.

These new perspectives may seem developed for natural systems and less relevant to the artificial systems created for manufacturing. However, the significant parameters of modern manufacturing are determined by its social role in a society of suppliers and consumers. In a recent keynote address, the Executive Vice President of NEC defined manufacturing as the "activity of processing and converting intellectual and physical raw materials and elements into hardware and software products for ease of consumer's use,". and emphasized total manufacturing systems with customers involved as much as employees (Uenohara 1986). He used the concept of a "virtual plant" as a worlwide distributed manufacturing process. In the same context the Chief Engineer of GMF Robotics noted that "what is wanted is a new science of manufacturing that integrates technology, management and economics" (Akeel 1986).

Expert systems, and their theoretical foundations in knowledge science (Gaines 1986b), are an essential component of a new science of manufacturing. The following section analyzes their relation to the total manufacturing system and the other information technologies involved.

4. INFORMATION SYSTEMS IN INTEGRATED MANUFACTURING

Figure 14 shows the information systems in a modern production unit using IMS techniques. The outer ring comprises eight basic information technologies that together support the IMS and its interface to the factory and business world. The centre shows the firm itself with its corporate structure, and the rings surrounding it show the human interfaces and communication protocols necessary for the systems' management and integrated operation. The figure has been simplified to the minimum structure necessary to support an effective IMS, and the residual complexity shows the need to consider the total context of IMS information technology. Such a system will not necessarily succeed if any one component, or even several, are advanced state-of-the-art technologies. However, it will certainly fail if one component is inadequate or the total system is not well-integrated.

4.1 THE FIRM

The central core is the non-technology part of the system, the people that manage and operate the plant, their organization and value systems. The overt operation of the IMS is part of the *technical culture* of the firm in Hall's (1959) terms. It can be communicated, documented and partially programmed. It can also be changed fairly readily in response to new requirements, techniques and technologies. The management structure of the firm is part of its *formal culture.* Only part of it is overt and documented and it is resistant to change. What has come to be called the "corporate culture" (Deal & Kennedy 1982) is in Hall's terms the *informal culture* of the firm. It pervades the organisation, is communicated by example, rarely documented, and changes only slowly or under pressures of survival.

The managerial structures and social processes of the firm are not normally treated as part of its information technology. However, it is possible to develop socio-cognitive models of organisations that encompass both the people and the information technology supporting them (Shaw & Gaines 1986a) and Hall's cultural model is significant to knowledge engineering for expert systems. In particular, in order to be successful the technical systems must be consistent with the organizational structures and processes. This applies particularly to inter-personal communications where computer networks will not be used if they violate the managerial and social norms of the firm, and to decision and control paths which have to conform to existing authority and procedures that are not necessarily those of the organization chart.

4.2 HUMAN-COMPUTER INTERFACE

Recognition that the managerial and social structure of the firm dominates its style of operation draws attention to human-computer interaction (HCI) as a critical technology. Advances in graphics, voice input/output and intelligent terminals have improved the technical repertoire for HCI (Gaines & Shaw 1984a, Shaw & Gaines 1985). Widespread contact with low-cost personal computers has increased computer literacy and user acceptance of the technology. The human factors of FMS systems are being studied (Mitchell, Govindaraj & Ammons 1984). However, much remains to be done to bring the human engineering of computer-based systems to the same level of professionalism as hardware and software engineering (Gaines & Shaw 1986a,b). For decision and control systems involving expert systems and simulation, information presentation and ease of communication are of prime importance. A technically powerful system will be wasted unless it is comprehensible and accessible to its users, and gives them confidence in the basis of its operations.

4.3 COMMUNICATION PROTOCOLS

The days of single-vendor, special-purpose systems designed against a static, well-defined specification are long gone. IMSs integrate all aspects of the operation of a firm, from its financial planning and accounting, through its inventory control, customer, order, delivery and payment records, production planning, scheduling, control and monitoring, to its liaison with other organizations concerned with distribution, marketing, environmental control, and so on. Equipment from many vendors, purchased at different times, for different purposes, by different parts of the organisation, has to operate together. In this lies the major practical obstacles to the creation of effective IMSs at present.

The technical problems are beginning to be resolved at the lower levels by the adoption of industry standards in communication protocols such as the open systems interconnection (OSI) standard (Day & Zimmerman 1983), the provision in data-processing and database packages for the import and export of data from "foreign" systems, and the provision of data-communications for parameter-setting and data-collection in control and instrumentation systems. These alone are necessary but not sufficient to allow the

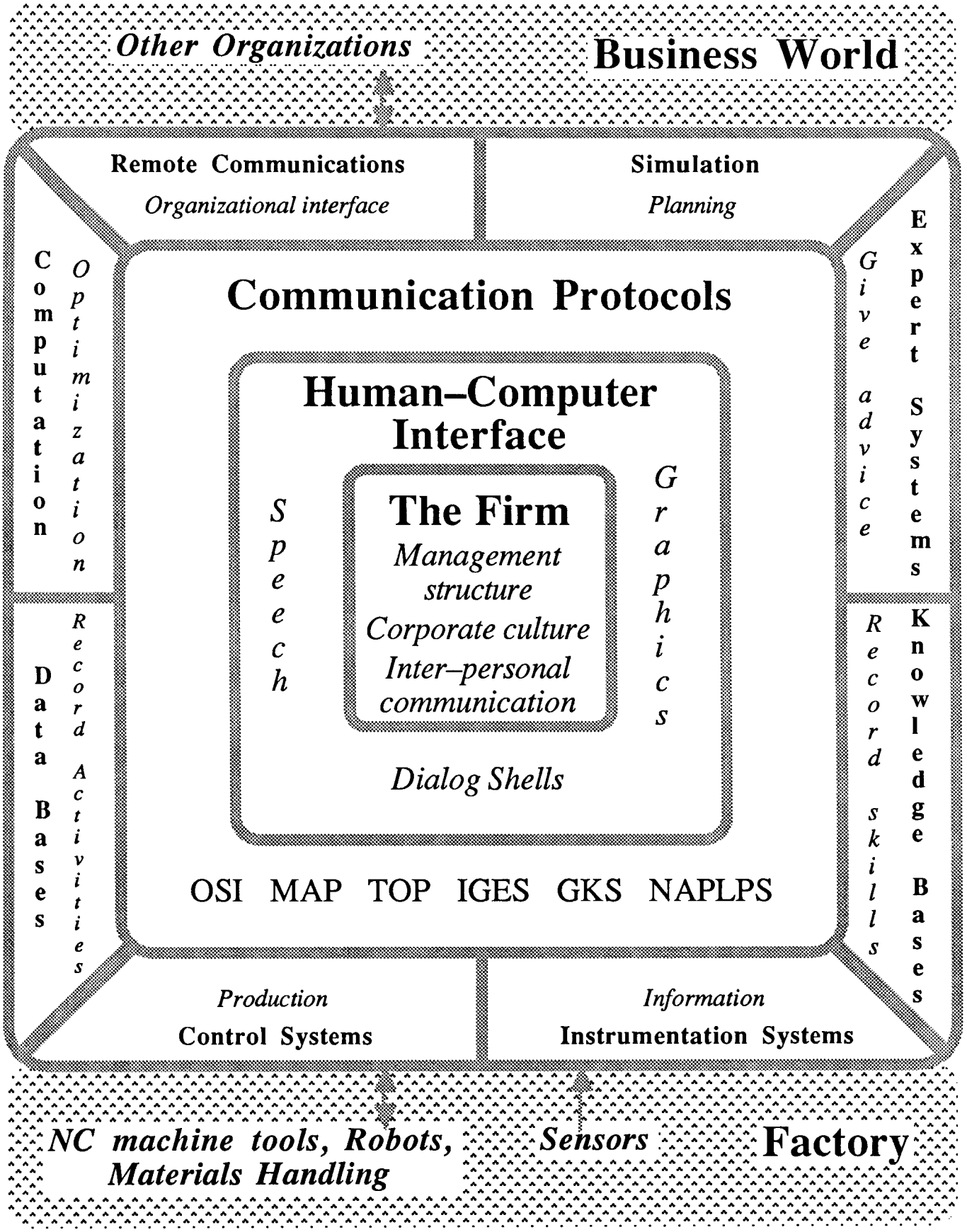

Fig.14 The technologies involved in an integrated manufacturing system

widespread creation of IMSs. They provide a syntactic framework for system integration but no coherent semantics in which to express it.

The *manufacturing automation protocol* (MAP) has been developed to give application-level semantics to the OSI standard by General Motors (1984) as the major corporation most affected by IMS developments. It was sponsored by the GM Engineering and Manufacturing Computer Coordination activity in late 1979, placed in the public domain as a cooperative effort across computing, manufacturing equipment and manufacturing industries, and has attracted widespread industry support. MAP defines an application-layer protocol for OSI specific to IMS requirements. It is particularly significant in system design in offering the capability to collect operational and performance data on a scale, and with a richness of context, impracticable currently (McCarthy 1985).

4.4 THE APPLICATIONS RING: BASIC TECHNOLOGIES

The outer ring in Fig. 14 shows the main information technologies in IMSs and their typical applications. Moving counter-clockwise around the ring:

Remote Communications are necessary to interface the factory with its suppliers and consumers. A particular firm is part of an industrial infrastructure each part of which is trying to optimize its productivity, profitability and stability. This can best be achieved if suppliers are aware of consumers' needs and projected needs and consumers are aware of the production and delivery schedules of suppliers.

Computation Systems perform the classical number-crunching tasks under the control of algorithms that with modern software engineering have a high degree of accuracy, conformity to specification and reliability.

Database Systems have become the classic core of a firm's information system, recording all its activities in a co-ordinated fashion and making the information available on a controlled basis to those systems and people with a legitimate need to know.

Control Systems began to be integrated with information systems as numerically-controlled machine tools came into use and with the development of industrial robots capable of part-handling, tool-changing and materials movement, total automation of production has come into widespread use.

Instrumentation Systems have had to increase in capability to compensate for the fewer people observing the manufacturing process and the increased need for timely information on the state of the plant, tool wear, and so on, to enable the IMS to optimize overall operation.

4.5 THE APPLICATIONS RING: BASIC TECHNOLOGIES

Three technologies in the outer ring of Fig. 14 are particularly relevant to decision aids for planning IMSs.

Knowledge Bases are distinguished from databases by containing inference rules rather than facts. The rules may necessarily be heuristic in nature, generating plausible advice rather than hard facts. If databases may be said to record a firm's activities then knowledge bases may be said to record its skills, particularly its management skills.

Expert Systems are the means to apply a knowledge base to the solution of a particular problem. They stand in relation to the knowledge base as does conventional computation to the data base. They differ in that their role as advisors and dependence on heuristics makes accountability and comprehensibility of major importance. An ES has to be able to justify and explain the basis of its advice.

ES technology can be applied at a number of levels in IMSs including product design (Kim & Suh 1985), FMS justification (Sullivan & LeClair 1985), job-shop scheduling (Fox 1985), simulation (Bruno, Elia & Laface 1985), on-line process control (Brown et al 1985) and robot control (Kirschbrown & Dorf 1985). However, the problem of major concern is the design stage at which the IMS has to be specified in terms of its performance and a range of diverse machine tools have to be brought together in an integrated system design. This stage presents a number of major conceptual difficulties currently that are impeding the rapid diffusion of IMS technology into appropriate industries. It is typical of the problems that because of their complexity and diffuseness they have to be "managed" and are very susceptible to support through ESs (Hayes-Roth 1984).

Simulation has been separated from other forms of computation because it is computation based on a model of some other system and it is the relation of the simulated model results to that of the system modeled that is of paramount importance. The models used in simulation to infer the behavior of a system are generally deeper than the models used in ESs to infer the proper advice about a system, even though both may be concerned with the same system (Gaines & Shaw 1985a, Shannon, Mayer & Adelsberger 1985).

Simulation technology can be applied at a number of different levels in IMS (Smith 1985). However, the planning stage for flexible manufacturing is one of the most significant (Wortman & Miner 1985). A FMS involves the integration of a number of different tools, probably from different manufacturers and possibly in a way not previously encountered by the manufacturers. There is a variety of semi-standard FMS configurations recommended or used to demonstrate possibilities but the permutations required in practice go far beyond these. A FMS usually involves the integration of new technologies with older ones. The newer technologies are particularly in materials handling (Mangold 1981, Edson 1984) and in computer-based communication and software support for the overall system (Bruno, Demartini & Velanzano 1984). These are not well-understood and problems of matching flow-rates between machines, and data-rates and formats between equipment controllers, are severe. Simulation provides a manager with a way of experimenting with configurations and coming to understand the potentials of different tools (Gaines 1986a, Wichmann 1986).

The interactive decision-making process supported by ESs and simulation is a natural way in which to manage FMS implementation. It would seem feasible to ascertain the requirements and then use non-interactive computation to provide an optimal solution, but requirements are rarely well-defined and hard. Usually, a number of possibilities are open which are of diverse types, such as manufacturing at alternative sites or using different tools and sequencing. It is also often the case that the requirements are soft in that they will change as the simulation and decision process proceeds and the manager comes to understand the problem space better. These considerations are not so much defects of the human decision process as limitations of decision systems that do not have adequate sensitivity analysis. If a designer knew in using an algorithm for grouping tools that a particular constraint he had applied was reducing the throughput by 20% then he might relax that constraint. However, it would place an excessive burden on the decision maker to require that all such trade-offs were specified in advance. The relevant "what-if"s constitute only a small sub-set of all possibilities. Interactive, sequential decision-making is an efficient method for determining such relevance.

5. CONCLUSIONS

Developments in computers, robotics, communications, electronics and materials are occurring at an increasing pace and have widespread impact on industrial manufacturing processes. In particular the combination of these new technologies offers opportunities for integrated manufacturing systems that increase productivity through improved reliability, reproducibility, flexibility, human factors and cost/effectiveness. IMSs are applicable to a spectrum of industry from comparatively small firms up to large organizations. However, it is difficult for firms to keep up with the flow of information and experience on these rapidly changing new technologies.

Decision support systems for IMSs present particular problems for today's ES technology because manufacturing involves the dynamics of physical processes and requires knowledge-based systems that combine simulation techniques with those of current ESs. They also present challenges in coordination because the expertise required is dispersed across a number of disciplines, between universities and industry, and between equipment manufacturers and users. However, the relevant technologies and knowledge are now at a stage where practical systems may be developed. The refinements of these systems through experience in their use, further analysis and data collection, will lead to the evolution of the totally-integrated manufacturing system.

6. ACKNOWLEDGEMENTS

Financial assistance for this work has been made available by the National Sciences and Engineering Research Council of Canada. I am grateful to my colleagues, Drs Kolodny, Moray, Shaw, Turksen and Vanelli for discussion and comments.

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